Bias in the Air: A Nationwide Exploration of Teachers' Implicit Racial Attitudes, Aggregate Bias, and Student Outcomes

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Theory suggests that teachers' implicit racial attitudes affect their students, but large-scale evidence on U.S. teachers' implicit biases and their correlates is lacking. Using nationwide data from Project Implicit, we found that teachers' implicit White/Black biases (as measured by the implicit association test) vary by teacher gender and race. Teachers' adjusted bias levels are lower in counties with larger shares of Black students. In the aggregate, counties in which teachers hold higher levels of implicit and explicit racial bias have larger adjusted White/Black test score inequalities and White/Black suspension disparities.

Keywords: achievement gap; achievement inequality; correlational analysis; descriptive analysis; disparities; hierarchical linear modeling; implicit racial bias; race; school discipline disparities; teacher bias; teacher cognition

A vast literature in education shows that teachers treat students differently based on student race and that such differential treatment can affect students' learning (R. F. Ferguson, 2003; Tenenbaum & Ruck, 2007). In a separate literature, social psychologists have demonstrated that people hold "implicit racial biases," or biases that lie outside conscious awareness. Measures of implicit bias correlate with various biased behaviors (Greenwald et al., 2009), especially when geographically aggregated (Payne et al., 2017). Education researchers have thus begun measuring teachers' racial biases to better understand how they affect students, but these studies are few in number, small scale, and mostly situated outside the United States (Warikoo et al., 2016). Thus, the basic descriptive facts about teachers' implicit racial biases and their correlates that will help advance theory of implicit racial bias in education are lacking. In the present study, we used data from three large-scale nationwide data sources to help fill this gap.

Background

Implicit bias is mediated by a process of implicit cognition (Greenwald & Krieger, 2006). Cognition is "implicit" when it takes place outside of one's conscious attentional focus (Greenwald & Krieger, 2006). Two forms of implicit cognition relevant to race include implicit attitudes (the tendency to like or dislike members of a racial group) and implicit stereotypes (the association of a group with a particular trait; Greenwald & Krieger, 2006). Implicit attitudes and stereotypes can be automatically activated in one's mind (Devine, 1989), leading to implicit bias, or prejudicial behaviors or judgments (Greenwald & Krieger, 2006). Thus, people can exhibit implicit bias even when they do not consciously endorse the underlying attitude or stereotype (Devine, 1989; Dovidio et al., 2002).

Because implicit attitudes elude conscious awareness, they require special methods of measurement. The most widely used measure of implicit racial bias is the implicit association test (IAT). The White-Black IAT assesses the relative strength of one's implicit associations between European Americans[1] and an attitude or stereotype relative to the strength of one's associations for African Americans through response times on a series of computerized categorization tasks (Greenwald et al., 2009). Numerous studies have shown IAT performance correlates with racially biased behaviors in individual-level and geographically aggregated data (Green et al., 2007; Greenwald et al., 2009; Hehman

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et al., 2018; Leitner et al., 2016; McConnell & Leibold, 2001; but for a different take on the evidence, see Oswald et al., 2013).

Implicit Racial Bias and Educators

Educators' implicit racial biases are of particular interest due to their potential consequences for students (Quinn, 2017; Starck et al., 2020; Warikoo et al., 2016). Findings from noneducational settings (Dovidio et al., 2002) lead one to expect that teachers' negative implicit attitudes toward different racial groups will influence their demeanor and warmth when interacting with students and families from those groups. These cues are often detectable (Dovidio et al., 2002) and can communicate a lack of interest or confidence in students, in turn inhibiting the development of relationships conducive to learning (Babad, 1993).

Teachers with implicit biases are liable to provide biased evaluations of students' academic performance or potential, which can negatively impact Black students through self-fulfilling prophecies (Papageorge et al., 2016) or by triggering stereotype threat (Steele & Aronson, 1995). Students are generally good at perceiving teachers' expectations (McKown et al., 2010), and students as young as 6 years can recognize when people hold stereotypes (McKown & Weinstein, 2003). This may not only impede performance in the short term but also can diminish learning in the long term, either through stress (Taylor & Walton, 2011) or by inducing challenge avoidance, disidentification with school, and rejection of teacher feedback (Perry et al., 2003; Steele & Aronson, 1995).

Educators' implicit biases may also contribute to the well-documented racial disparities in school discipline outcomes (Gregory et al., 2010) by affecting the way in which educators interpret students' behaviors or the severity of the punishments they deliver. Evidence suggests that Black students are often disciplined for more subjective infractions, such as "disrespectful behavior" or acting "disruptively," whereas White students are often disciplined for more objective infractions, such as smoking or vandalism (Skiba et al., 2002). Educators with stronger implicit biases may be more likely to interpret Black students' behaviors as threatening and hence dispense discipline (A. A. Ferguson, 2000), which can negatively affect student learning and other life outcomes (Gregory et al., 2010; Lacoe & Steinberg, 2019).

Measuring implicit bias in education. Despite theoretical support for its influence in education, few researchers have directly measured teachers' implicit racial biases in the United States. Studies from outside the United States have shown that teachers' levels of implicit bias (as measured by the IAT) toward racial/ethnic minorities is associated with test score inequalities within teachers' classrooms (Peterson et al., 2016; van den Bergh et al., 2010), and similar results have been found for gender bias (Carlana, 2019). In the United States, teachers and nonteachers exhibit similar levels of implicit bias overall (Starck et al., 2020), and teachers with higher levels of racial bias on the IAT were less likely to report that they promoted mutual respect among students in their classrooms (Kumar et al., 2015). In an experimental study, Black—but not White—college students learned less when taught by a White college student with higher levels of implicit racial bias (as measured by a subliminal priming task), and this effect seemed to be mediated by instructor anxiety and instructional quality (Jacoby-Senghor et al., 2016).

Aggregate Implicit Bias

Several studies, mostly occurring in noneducational contexts, have shown implicit bias scores from the IAT to more strongly correlate with racial disparities when aggregated to the level of nation, U.S. state, or county/metropolitan area. For example, researchers in the United States have found aggregated implicit (and explicit) bias scores to be associated with county-level rates of cardiovascular disease among Black residents, greater Black-White disparities in infant health outcomes, and disproportionate use of lethal force by police (Blair & Brondolo, 2017). Aggregate implicit bias also explains some of the geographic variation in racial differences in economic mobility (Chetty et al., 2018). In the field of education, Nosek and colleagues (2009) showed that country-level implicit stereotypes dissociating women with science correlated with country-level gender disparities on international math and science assessments. In the most relevant study to our work, Riddle and Sinclair (2019) found that county-level estimates of White respondents' biases are associated with disciplinary disparities between Black and White students.

To interpret findings on aggregate bias, social psychologists have proposed the "bias of crowds" theory (Payne et al., 2017). In this perspective, implicit bias is not a stable trait of individuals. Instead, implicit bias is conceived of as "a social phenomenon that passes through the minds of individuals" that "exists with greater stability in the situations they inhabit" (Payne et al., 2017, p. 236). The extent to which an individual exhibits bias will vary across contexts due to differential concept accessibility across those contexts (Payne et al., 2017). Concept accessibility is "the likelihood that a thought, evaluation, stereotype, trait, or other piece of information will be retrieved for use" in cognitive processing (Payne et al., 2017, p. 235). For racial bias in particular, this refers to the ease of accessing negative evaluations or associations when a racial category is activated in one's mind. According to this theory, some portion of an individual's IAT score reflects concept accessibility in the broader culture, some portion reflects influences encountered shortly before the test, and some portion reflects intermediate influence, or shared concepts that may be made more accessible in some contexts than others. When individuals' bias scores are aggregated, the idiosyncratic influences wash away, and variation in average scores will reflect the contextual influences with the most widely shared accessibility (Payne et al., 2017). Measures of implicit bias are therefore better measures of situations than of individuals and will consequently be more predictive in aggregate.

In our study, we built on limited previous work on aggregate implicit bias in education in two primary ways. First, we considered racial test score differences as outcomes. Despite growing evidence connecting disciplinary and achievement gaps (Pearman et al., 2019), limited work has investigated the influence of racial bias on the latter outcome (an exception is a recent working paper in which Pearman [2020] considered similar test score models to ours). Furthermore, unlike prior work, we disaggregated regional estimates of bias to specifically explore the biases of teachers. We identified the correlates of teachers' biases and also their relationship to key disparities.

Summary and Research Questions

Theory from social psychology suggests that teachers' implicit racial biases contribute to racial disparities in academic and school disciplinary outcomes. Initial studies have demonstrated the potential value of greater incorporation of theory and measures of implicit biases into education research. Yet a basic descriptive picture of teachers' implicit biases and their correlates is lacking. In this study, we therefore address the following research questions:

Research Question 1: How do teachers' implicit racial White/Black biases vary across the United States? Do individual characteristics correlate with teacher implicit bias? Do contextual variables (e.g., racial composition and average socioeconomic status) or instructional variables (e.g., racial differences in student/teacher ratios) correlate with teachers' implicit biases?

Research Question 2: Does county-level implicit and explicit White/Black bias (pooling teachers and nonteachers) correlate with racial disparities in test scores or disciplinary outcomes? Does teacher county-level bias correlate with such disparities?

Methods

Data

We drew from several data sources to answer our research questions. A key data source was Project Implicit, an archive of Internet volunteers who visited the Project Implicit website (Xu et al., 2014). The data include visitors' scores on the White/Black IAT and responses to survey items including explicit racial attitudes, demographics, and occupation.[2] The data file contains FIPS county identifiers, enabling us to merge individual- and county-level bias data with data from the Stanford Education Data Archive (SEDA; Reardon, Ho, et al., 2019) and the Civil Rights Data Collection (CRDC).

Project Implicit

The White/Black IAT. The White/Black IAT provides *d* scores indicating how much more strongly the respondent associates "African American" with a negative valence and "European American" with a positive valence versus associating "African American" with a positive valence and "European American" with a negative valence. Positive scores indicate an implicit preference for European Americans, negative scores indicate the reverse, and a score of zero indicates neutrality. Cut scores of ±.15, .35, and .65 are used to distinguish between *little or no, slight, moderate*, and *strong* biases (Project Implicit, n.d.). We used only IAT data from (self-reported) first-time test-takers to avoid including multiple measurements from the same individual and to improve comparability of scores across respondents. We also included only respondents who visited the Project Implicit website during the academic years overlapping with our student outcome data (i.e., July 2008–June 2016).

Explicit bias. The Project Implicit website administers feeling thermometer items (11-point scale of how cold, neutral, or warm respondents feel toward particular racial groups). For each respondent, we created an explicit bias score by subtracting the respondent's rating of Black people from their rating of White people.

Stanford Education Data Archive. The SEDA test score data set (Version 3.0) contains average student standardized test scores for school districts across the United States over the 2008–2009 academic year through the 2015–2016 academic year (Fahle et al., 2019). These data were assembled using the ED*Facts* data system, which contains math and English language arts (ELA) scores for third through eighth graders, disaggregated by student race/ethnicity. For this study, we used estimates of the standardized mean difference in test scores between White and Black students, aggregated across grades, subjects, and school years to the county level.

We merged test score data to measures from the SEDA covariate data set (Version 3.0) to include county-level controls in analyses. To maintain consistency with models used by Reardon, Kalogrides, and Shores (2019), we also employed several control measures from an earlier version (Version 2.1) of the SEDA covariate file. This version contains a wider range of covariates but, unlike the SEDA test score data set, does not incorporate district data from the 2015–2016 school year. We organized covariates into two main groups: general covariates, which include demographic, socioeconomic status (SES), and instructional controls, and disparity covariates, which include White-Black differences on SES and instructional controls. In Appendix A (in the Supplemental Material available on the journal website), we provide more detail on differences between versions of the SEDA covariate data set and the controls we used. For detail on how variables were compiled and for which counties, see Fahle et al. (2019).

Civil Rights Data Collection. We merged the Project Implicit data with data from the U.S. Department of Education's CRDC using county identifiers. The CRDC collects school-level data from all school districts in the United States. The data contain school-level enrollment counts by race/ethnicity along with counts by race/ethnicity of students who received at least one in-school or out-of-school suspension over the 2011–2012, 2013–2014, and 2015–2016 school years. We aggregated these counts to the county level over the three school years, then merged the county-level suspension data with (a) county-level bias data from Project Implicit (described in the following) and (b) the aforementioned county-level covariates from SEDA.

Samples

For ease of comparison, we applied the same initial sample restrictions for each research question (with additional required restrictions outlined in the analytic plan). Specifically, when exploring the correlates of teachers' biases (Research Question 1) and the relationship between teacher biases and student outcomes (Research Question 2), we restricted our analyses to counties that met the following criteria: have Project Implicit teacher respondents with demographic data and implicit bias scores, have county-level bias estimates, have SEDA test score gap data, have CRDC disciplinary gap data, and have all key county-level covariate data. After these restrictions, we preserve approximately 76% of the 2,282 counties with at least one K–12 teacher IAT respondent and approximately 82% of the 2,109 counties with both achievement and disciplinary gap data.[3] Furthermore, Tables C1, C2, and C3 in Appendix C (in the Supplemental Material available on the journal website) show that our results for teacher bias are robust to alternative sample restrictions. In Table C4 of Appendix C (in the Supplemental Material available on the journal website), we used American Community Survey data to show that although our sample counties are more populated, key demographic and economic indicators are similar to counties omitted; however, because of our sample restrictions, we caution against generalizing findings to the approximately 3,000 counties in the United States more broadly.

In Table 1, we present descriptive statistics for K–12 educators in our common sample (along with comparisons to national estimates when available). Sample teachers are slightly less likely to be female (71% vs. 77%), more likely to be Black (9% vs. 7%), and more likely to hold a master's degree (59% vs. 57%) compared to national estimates.

Analytic Plan

Research Question 1: Correlates of teachers' implicit biases. To address Research Question 1, we used responses from K–12 educators in the Project Implicit data to fit multilevel models of the form:

$$Y_{ics} = \alpha_{cs} + \alpha_s + X'_{ics}\Gamma + C'_{cs}\Theta + \gamma + \epsilon_{ics}, \quad (1)$$

$$\alpha_{cs} \sim N\left(\mu_{cs}, \sigma_{cs}\right) \perp \alpha_s \sim N\left(\mu_s, \sigma_s\right) \perp \epsilon_{ics} \sim N\left(0, \sigma_\epsilon\right),$$

where Y_{ics} is the IAT score for teacher i in county c in state s (including Washington, D.C.); α_{cs} and α_s are random intercepts for county and state, respectively, X'_{ics} is a vector of respondent-level controls (including sets of mutually exclusive dummy variables for race/ethnicity, gender, age category, and education level); C'_{cs} is the vector of contextual and instructional variables from the SEDA data similar to those used in Reardon, Kalogrides, and Shores (2019) described in our Appendix A (in the Supplemental Material available on the journal website); and γ is a set of school-year fixed effects. To understand how educators' implicit biases vary across the United States, we fit Model 1 without X'_{ics} and C'_{cs} and report the county- and state-level intraclass correlations (ICCs). In Appendix F (in the Supplemental Material available on the journal website), we include analyses comparing biases of educators and noneducators.

Research Question 2: Aggregate implicit (and explicit) White/Black biases correlating with racial disparities in test scores and suspensions

Test scores. To investigate the relationship between implicit racial bias and student test scores, we first obtained county-level empirical Bayes (EB) bias predictions adjusted based on: (a) the (non)representativeness of the IAT respondent sample compared to the actual population and (b) the differences in reliabilities of predictions across counties. We specifically used a multilevel regression and poststratification (MrP) approach (Hoover & Dehghani, 2019; for more detail, see Appendix D in the Supplemental Material available on the journal website) to perform this adjustment. In our MrP model, we used the county-level joint distributions for age, gender, and race from the American Community Survey (2015 five-year estimates) to adjust our pooled bias scores.

We are unaware of any single source that provides nationwide county-level data on teacher demographics, complicating the poststratification of county-level estimates of teacher bias. We thus searched for these data online for each state to varying degrees of success. With few states reporting joint distributions, we focused on identifying county-level breakdowns of teacher race (i.e., White, Black, or other race) given that individuals' race significantly correlated with their biases in our analyses. With the available data, we employed MrP and adjusted the county-level teacher bias scores used in analyses. In Table D (in the Supplemental Material available on the journal website), we document the 20 states (including Washington, D.C.) for which we found these data (these adjustments resulted in smaller county-level samples sizes for the models using teacher bias EBs as predictors).

To make coefficients more interpretable, we rescaled adjusted EBs for bias as z scores at the county level. We then included either pooled or teacher county-level EBs, $\hat{\delta}_j$, as controls in the following model:

$$\widehat{Y_{cs}} = \alpha + \hat{\delta}_{cs}\beta + C'_{cs}\Theta + \gamma_s + \varepsilon_{cs} + \chi_{cs}, \quad (2)$$

$$\varepsilon_{cs} \sim N\left(0, \sigma_{\varepsilon_{cs}}\right),$$

$$\chi_{cs} \sim N\left(0, \widehat{\phi^2_{cs}}\right).$$

In Equation 2, $\widehat{Y}_{cs}$ represents the estimated standardized mean White-Black test score difference (across subjects and years) in county c (using the cohort standardized scale in SEDA). We fit this model using meta-analytic techniques to account for known variation in the precision of these estimated racial test score differences across counties; χ_{cs} reflects the sampling error in $\widehat{Y_{cs}}$ with known variance $\widehat{\phi^2_{cs}}$. We included county covariates, C'_{cs}, similar to those used by Reardon, Kalogrides, and Shores (2019) to explain regional variation in White-Black test score disparities; γ_s represents a vector of state fixed effects. β thus represents our coefficient of interest—the relationship between county-level bias and test-score disparities. Finally, we fit models replacing implicit-bias EBs with explicit-bias EBs.

Table 1
Descriptive Statistics for K–12 Educators

	M	*SD*	Nationwide
Respondent-level Project Implicit data (*N* respondents = 39,776, *N* counties = 1,730)			
Age < 30	0.389		Average age: 42.4
Age 30–39	0.287		
Age 40–49	0.175		
Age 50–59	0.106		
Age 60–69	0.037		
Age 70+	0.006		
American Indian	0.004		0.004
White	0.807		0.801
Black	0.089		0.067
Black+White	0.013		
East Asian	0.010		0.025 (APIA)
Multiracial	0.032		0.014
Native Hawaiian	0.003		
Other race (unspecified)	0.040		
South Asian	0.006		
Education: elementary–some high school	0.006		
Education: high school degree	0.008		
Education: some college/associate's degree	0.086		
Education: bachelor's degree	0.261		0.405
Education: master's degree	0.590		0.573
Education: advanced degree	0.049		
Female	0.714		0.766
IAT *d* score	0.324	0.455	
2008–2009 school year	0.159		
2009–2010 school year	0.142		
2010–2011 school year	0.096		
2011–2012 school year	0.085		
2012–2013 school year	0.086		
2013–2014 school year	0.099		
2014–2015 school year	0.178		
2015–2016 school year	0.155		
County-level OCR data (*N* counties = 1,730)			
Student enrollment: Black	12,999.300	43,638.000	
Student enrollment: White	39,335.700	62,351.800	
Probability in-school suspension: Black	0.144	0.080	
Probability out-of-school suspension: Black	0.133	0.060	
Probability in-school suspension: White	0.062	0.039	
Probability out-of-school suspension: White	0.046	0.029	
County-level SEDA test data (*N* counties = 1,730)			
Mean White-Black test score difference (standardized)	0.542	0.225	
County-level SEDA covariate data (*N* counties = 1,730)			
SES composite (all)	–0.083	0.647	
Proportion Black in public schools	0.153	0.198	
Proportion Hispanic in public schools	0.124	0.158	
Between-school free lunch/not free lunch segregation	0.078	0.076	
Between-school Black/White segregation	0.151	0.121	
Proportion attending charter schools	0.021	0.048	
Per-pupil instructional expenditures in average student's school (in $10,000)	0.596	0.151	
Average student-teacher ratio	16.282	16.818	
White-Black gap in SES composite	2.297	0.667	
White-Black school free-lunch rate difference	–0.082	0.100	
White/Black relative student-teacher ratio	1.013	0.086	
White-Black charter school enrollment rate difference	0.006	0.033	

Note. Variables in rows without reported standard deviations are binary indicator variables for the row name. Statistics for the Nationwide column came from the National Teacher and Principal Survey (2015–2016) and include estimates for only public school teachers. SES = composite measure of socioeconomic status (composed of log median income, poverty rates, unemployment rates, proportion households receiving SNAP, proportion single-mother-headed households, proportion 25+ with bachelor's degree or higher). APIA = Asian and Pacific Islander American; IAT = implicit association test; OCR = Office of Civil Rights; SEDA = Stanford Education Data Archive.

Suspensions. Our preferred models for examining the relationship between geographic-area White/Black biases and White/Black school discipline disparities are logistic regression models of the form:

$$P\left(Y_{ics}=1 \mid \boldsymbol{C}_{cs}'\Gamma\right)=\frac{1}{1+\exp\left(-\left(\begin{array}{l}Black_{ics}\alpha+\hat{\delta}_{cs}\beta+\\ \left(Black_{ics}\times\hat{\delta}_{cs}\right)\mu+C_{cs}'\,\Gamma+\gamma_{s}\end{array}\right)\right)}. \quad (3)$$

The outcome, Y_{ics}, is an indicator for whether student i in county c was suspended one or more times in a given school year, with separate models for in-school and out-of-school-suspensions. $Black_{ics}$ is an indicator for whether student i is Black (vs. White; we excluded other racial groups), $\hat{\delta}_{cs}$ again represents adjusted county-level EBs (rescaled as *z* scores for either pooled or teacher bias scores), and γ_s represents state fixed effects. We fit models with and without the SEDA county-level covariates, C_{cs}'. Note that the CRDC data are not student-level data; rather, we mimic student-level models by pooling suspension data within county across school years and summing the frequency counts, then applying these counts as frequency weights to the aggregated data (for details, see Appendix B in the Supplemental Material available on the journal website).

The coefficient of interest, μ, expresses whether the relationship between county-level White/Black bias (either pooled or for teachers only) and suspension probability differs for Black and White students. We hypothesize the $\hat{\mu}$ coefficients across models would be positive and statistically significant. Again, we fit additional models that replaced implicit-bias EBs with explicit-bias EBs. To account for correlated errors across individuals within geographic regions, we clustered standard errors at the county level (i.e., the level to which implicit bias is aggregated; for qualitatively similar results when clustering standard errors at the state level, see Appendix E in the Supplemental Material available on the journal website).

Results

Educators' Implicit Racial Biases

Geographic variation. In Column 1 of Table 2, we present the results from the simple multilevel model with K–12 educators' IAT scores as an outcome (conditional only on year fixed effects). On average, K–12 educators hold "slight" anti-Black implicit bias (*d* score = .35 in the baseline year, see intercept). Most of the variation in these biases lies within county, with approximately 2% lying between counties and 0.6% lying between states (see ICCs in bottom rows).

Individual and contextual correlates. In Column 2 of Table 2, we added dummy variables for teacher gender (female vs. not female), race/ethnicity, age range, and education level. Controlling for everything else, female teachers showed slightly lower levels of bias than nonfemales (–.023). In many cases, teachers of color showed lower average bias than White teachers (whose mean *d* = .38, not shown), with Black teachers showing the lowest levels (average *d* score of approximately –.04, not shown). As a set, the teacher-level measures reduced the county-level ICC to approximately 1 percentage point. Contextual variables (Column 3) reduced county-level variation by a similar amount, with lower levels of teacher bias particularly found in counties with larger shares of Black students (controlling for other contextual factors). The instructional variables (i.e., expenditures and student-teacher ratio) were not generally associated with teacher bias. As seen in Column 4, coefficients for teacher-level variables were largely unaffected by the inclusion of the full set of contextual controls.

Racial Bias and Student Achievement

In Table 3, we present results from models regressing county-level test score inequality on county-level implicit bias (Panel A) and explicit bias (Panel B). As seen in Column 1, we found significant negative unadjusted associations between test score inequality and pooled implicit or explicit bias scores (pooled across all Project Implicit site visitors). However, the adjusted associations when controlling for our general covariates (SES, demographics, instructional covariates) are statistically significant and positive (*b* = .0499 and *b* = .0326, for implicit and explicit bias, respectively; Column 2). That is, controlling for these contextual variables, White students score higher than Black students in counties with higher levels of pro-White/anti-Black implicit and explicit bias. However, once we included the disparity covariates (White/Black disparities on SES, instructional variables), these positive associations between bias and gaps attenuated to near zero (Column 3).

In Columns 4 through 8 of Table 3, we present results with the set of counties for which we can adjust teacher bias scores for sample representativeness. First, we replicated the analyses from Columns 1 and 3, again finding that higher pooled bias scores are associated with smaller test-score differences when omitting contextual controls (Column 4) but less so when including contextual controls (Column 5). For teacher biases in particular (Columns 6–8), we found similar patterns: significant negative unadjusted associations between White-Black test-score inequalities and teachers' county-level implicit (*b* = –.058) and explicit (*b* = –.057) biases (Column 6) but significant positive associations once we entered the general controls (Column 7) and the disparity controls (Column 8). Specifically, controlling for everything else in the model, a 1 *SD* unit difference in county-level implicit bias of teachers is associated with approximately a .037 *SD* unit difference in White-Black test score disparity (.025 *SD* adjusted association for explicit bias). For reference, this represents approximately 6.7% of the average test score disparity (.54 *SD*) in our sample counties (see Table 1).

Racial Bias and Discipline Outcomes

In our sample, Black students are more than twice as likely to receive one or more suspensions (in-school and out-of-school) than White students in the average county; for in-school suspensions, the rates are 14% and 6%, respectively, and for out-of-school suspensions, the rates are 13% and 5% (see Table 1).

Table 2
Multilevel Models With IAT Score Outcomes, K–12 Educators Only

	1	2	3	4
American Indian		–.0843*		–.0857*
		(.0340)		(.0340)
East Asian		–.00644		–.00568
		(.0220)		(.0220)
South Asian		–.0964**		–.0934**
		(.0293)		(.0293)
Native Hawaiian		–.125**		–.125**
		(.0408)		(.0407)
Black		–.435***		–.429***
		(.00790)		(.00802)
Black+White		–.219***		–.219***
		(.0192)		(.0192)
Other multiracial		–.144***		–.143***
		(.0124)		(.0124)
Race: other/unknown		–.0946***		–.0943***
		(.0113)		(.0113)
Female		–.0231***		–.0233***
		(.00486)		(.00486)
Age: 30–39		–.0162**		–.0173**
		(.00568)		(.00568)
Age: 40–49		–.0357***		–.0374***
		(.00663)		(.00663)
Age: 50–59		–.0224**		–.0238**
		(.00794)		(.00794)
Age: 60–69		–.0170		–.0185
		(.0121)		(.0121)
Age: 70+		.0433		.0423
		(.0290)		(.0290)
Education: high school degree		–.0000174		–.0000372
		(.0382)		(.0382)
Education: some college		.0225		.0224
		(.0301)		(.0301)
Education: bachelor's degree		–.0126		–.0105
		(.0296)		(.0296)
Education: master's degree		–.00878		–.00581
		(.0295)		(.0294)
Education: advanced degree		–.0217		–.0190
		(.0310)		(.0310)
SES composite			–.0118	–.00541
			(.00702)	(.00626)
Proportion Black			–.287***	–.0868***
			(.0283)	(.0263)
Proportion Hispanic			–.0279	.0206
			(.0271)	(.0243)
Info index FRL/not FRL			–.00249	.0274
			(.0486)	(.0427)
Info index White/Black			–.0534	–.0748
			(.0789)	(.0689)
Proportion charter			–.102	–.182**
			(.0649)	(.0592)
PPE instruction			.0264	–.00119
			(.0287)	(.0268)
Student/teacher ratio			.000544	.000679
			(.000627)	(.000568)
FRL: W-B			–.0323	–.0422
			(.0797)	(.0707)

(continued)

Table 2 (continued)

	1	2	3	4
Proportion charter: W-B			–.242**	–.148
			(.0911)	(.0829)
Student/teacher: W/B			–.113	–.0987
			(.0991)	(.0863)
SES composite: W-B			.00168	–.0120*
			(.00599)	(.00535)
Constant	.351***	.419***	.500***	.556***
	(.00837)	(.0303)	(.0906)	(.0840)
ICC county	.0202	.00988	.0103	.00822
ICC state	.00593	.00491	.00493	.00613

Note. All models include random intercepts for counties and states. Sample size for each column is 39,776 respondents and 1,730 counties. All models control for year fixed effects. SES = composite measure of socioeconomic status (composed of log median income, poverty rates, unemployment rates, proportion households receiving SNAP, proportion single-mother-headed households, proportion 25+ with bachelor's degree or higher); SES composite: W-B = White/Black differences on the SES composite; FRL: W-B = White/Black differences in school free-lunch rates; proportion Black = proportion of Black students in public schools; info index W/B = between-school White/Black segregation (measured by the Theil information index, which equals 0 when all schools in a district have the same racial composition as the district overall and 1 when schools contain only one racial group); info index FRL/not FRL = between-school free lunch/not free lunch segregation; PPE instruction = per-pupil instructional expenditures; student/teacher ratio = average student-teacher ratio; student/teacher: W/B = White/Black ratio for student-teacher ratios; proportion charter = proportion of public school students attending charter schools; proportion charter: W-B = White/Black differences in charter enrollment rates; ICC = intraclass correlations.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table 3
Metaregression Models Estimating the Associations Between County-Level Aggregate Implicit/Explicit Racial Bias and County-Level Racial Test Score Inequalities

	1	2	3	4	5	6	7	8
Panel A. Implicit bias								
Bias: all	–0.0489***	0.0499**	0.00290	–0.0652***	–0.0404*			
	(0.00625)	(0.0159)	(0.0136)	(0.00900)	(0.0190)			
Bias: teacher						–0.0575***	0.0508***	0.0366**
						(0.0102)	(0.0138)	(0.0119)
Panel B. Explicit bias								
Bias: all	–0.0496***	0.0326**	–0.0000754	–0.0679***	–0.0221			
	(0.00608)	(0.0122)	(0.0104)	(0.00914)	(0.0146)			
Bias: teacher						–0.0573***	0.0414**	0.0251*
						(0.00979)	(0.0130)	(0.0113)
Sample	Pooled	Pooled	Pooled	Teacher	Teacher	Teacher	Teacher	Teacher
N counties	1,730	1,730	1,730	764	764	764	764	764
General covariates		Yes	Yes		Yes		Yes	Yes
Disparity covariates			Yes		Yes			Yes

Note. Standard errors in parentheses. All models include state fixed effects. Outcome is county's mean standardized White-Black test score difference pooled across grades and subjects (cohort standardized scale). Bias measures are county-level empirical Bayes predicted means, standardized to county-level *SD* of 1 and mean of 0. The pooled sample consists of all counties used across analyses; the teacher sample consists of these counties but subset to those that with data available allowing us to adjust teacher bias scores based on representativeness (see Appendix D in the Supplemental Material available on the journal website). General covariates include: socioeconomic status composite (composed of log median income, poverty rates, unemployment rates, proportion households receiving SNAP, proportion single-mother-headed households, proportion 25+ with bachelor's degree or higher), percentage public school students Black, percentage public school students Hispanic, per-pupil instructional expenditure, student/teacher ratio, percentage public school students attending charter school, and segregation indices. Disparity covariates include: White-Black difference in socioeconomic status composite, White-Black difference in free lunch, White-Black difference in percentage charter, and White/Black ratio of student/teacher ratio. Estimated from a metaregression performed by methods of moments.
*$p < .05$. **$p < .01$. ***$p < .001$.

In Table 4, we present the more formal results from our logistic regression models. With regard to bias, without (Column 1) and with (Columns 2 and 3) our key county-level covariates, we found patterns consistent with our hypotheses: Higher levels of pooled aggregate implicit and explicit bias are associated with in- and out-of-school suspensions differentially for White

Table 4
Logistic Regression Models Estimating the Association Between County-Level Aggregate Implicit/Explicit Racial Bias and In- and Out-of-School Suspensions by Race

	1	2	3	4	5	6	7	8
Panel A: In-school suspensions on implicit bias								
Black	1.071***	1.140***	1.137***	1.043***	1.125***	1.068***	1.123***	1.120***
	(0.0228)	(0.0182)	(0.0180)	(0.0333)	(0.0219)	(0.0264)	(0.0252)	(0.0239)
Bias (all)	0.0873**	0.105~	0.0734	0.117**	0.0193			
	(0.0266)	(0.0606)	(0.0621)	(0.0420)	(0.117)			
Black × Bias (all)	0.0864***	0.162***	0.153***	0.0767*	0.147***			
	(0.0251)	(0.0228)	(0.0229)	(0.0377)	(0.0339)			
Bias (teacher)						0.126***	0.0340	0.0259
						(0.0379)	(0.0665)	(0.0667)
Black × Bias (teacher)						0.0671*	0.103***	0.0983**
						(0.0317)	(0.0299)	(0.0304)
Panel B: Out-of-school suspensions on implicit bias								
Black	1.395***	1.432***	1.429***	1.356***	1.417***	1.449***	1.411***	1.409***
	(0.0265)	(0.0215)	(0.0213)	(0.0361)	(0.0277)	(0.0328)	(0.0291)	(0.0290)
Bias (all)	–0.0964***	0.0722	0.0458	–0.0664*	0.105			
	(0.0240)	(0.0495)	(0.0522)	(0.0315)	(0.0725)			
Black × Bias (all)	0.0422	0.0763**	0.0698**	0.00901	0.0525			
	(0.0260)	(0.0259)	(0.0253)	(0.0355)	(0.0367)			
Bias (teacher)						0.0108	0.202***	0.204***
						(0.0461)	(0.0541)	(0.0536)
Black × Bias (teacher)						0.0412	0.0355	0.0306
						(0.0326)	(0.0301)	(0.0291)
Panel C: In-school suspensions on explicit bias								
Black	1.098***	1.150***	1.146***	1.094***	1.147***	1.105***	1.142***	1.138***
	(0.0209)	(0.0186)	(0.0183)	(0.0291)	(0.0230)	(0.0282)	(0.0270)	(0.0250)
Bias (all)	0.0969***	0.0689	0.0456	0.130***	0.0454			
	(0.0240)	(0.0440)	(0.0446)	(0.0366)	(0.0766)			
Black × Bias (all)	0.0964***	0.164***	0.154***	0.111**	0.157***			
	(0.0247)	(0.0240)	(0.0239)	(0.0340)	(0.0320)			
Bias (teacher)						0.135***	0.0544	0.0499
						(0.0337)	(0.0590)	(0.0591)
Black × Bias (teacher)						0.0735*	0.0974***	0.0938**
						(0.0308)	(0.0292)	(0.0290)
Panel D: Out-of-school suspensions on explicit bias								
Black	1.425***	1.442***	1.437***	1.415***	1.440***	1.499***	1.438***	1.438***
	(0.0238)	(0.0217)	(0.0214)	(0.0316)	(0.0291)	(0.0360)	(0.0332)	(0.0325)
Bias (all)	–0.0793***	0.0534	0.0367	–0.0529~	0.130*			
	(0.0234)	(0.0371)	(0.0371)	(0.0309)	(0.0519)			
Black × Bias (all)	0.0590*	0.0866***	0.0777**	0.0639~	0.0898**			
	(0.0245)	(0.0255)	(0.0249)	(0.0367)	(0.0333)			
Bias (teacher)						–0.0142	0.148***	0.140**
						(0.0357)	(0.0443)	(0.0427)
Black × Bias (teacher)						0.0960**	0.0698*	0.0691*
						(0.0347)	(0.0331)	(0.0317)
Sample	Pooled	Pooled	Pooled	Teacher	Teacher	Teacher	Teacher	Teacher
N	90,539,613	90,539,613	90,539,613	49,078,959	49,078,959	49,078,959	49,078,959	49,078,959
N counties	1,730	1,730	1,730	764	764	764	764	764
General covariates		Yes	Yes		Yes		Yes	Yes
Disparity covariates			Yes		Yes			Yes

Note. Standard errors clustered at the county level in parentheses. All models include state fixed effects. Models fit using aggregate County × Race data pooled over the 2011–2012, 2013–2014, and 2015–2016 school years with frequency weights to mimic models with student data pooled across years. Bias measures are county-level empirical Bayes predicted means standardized to mean = 0, $SD = 1$. The pooled sample consists of all counties used across analyses; the teacher sample consists of these counties but subset to those with data available allowing us to adjust teacher bias scores based on sample representativeness (see Appendix D in the Supplemental Material available on the journal website). General covariates include: socioeconomic status composite (composed of log median income, poverty rates, unemployment rates, proportion households receiving SNAP, proportion single-mother-headed households, proportion 25+ with bachelor's degree or higher), percentage public school students Black, percentage public school students Hispanic, per-pupil instructional expenditure, student/teacher ratio, percentage public school students attending charter school, segregation indices. Disparity covariates include: White-Black difference in socioeconomic composite, White-Black difference in free lunch, White-Black difference percentage charter, White/Black ratio of student/teacher ratio.
~$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

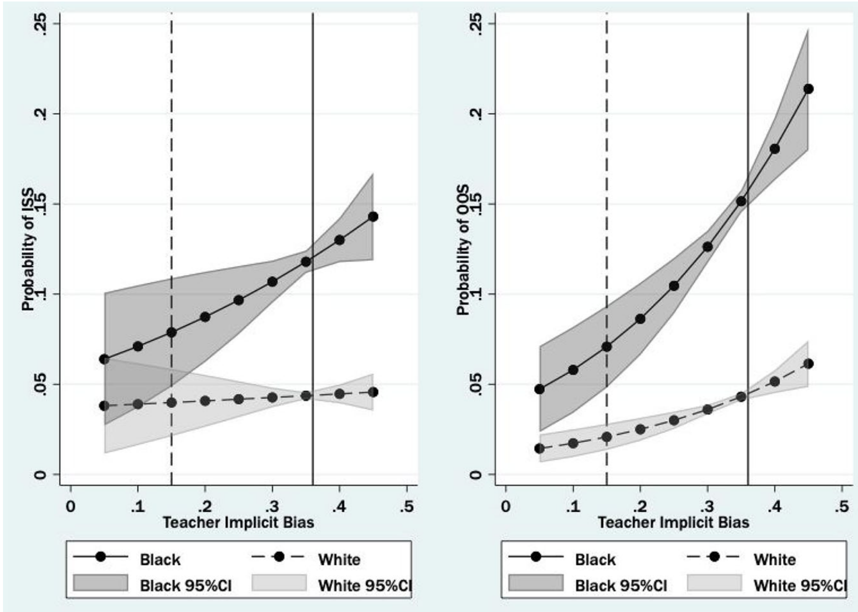

FIGURE 1. *Predicted probabilities for in-school suspension (ISS) and out-of-school suspension (OOS) by race against county-level teacher implicit bias (original IAT* d *scale) fixed at various values, adjusted for representativeness with values for contextual controls set at the mean.*
Note. The solid black vertical line identifies the county-level mean for teacher implicit bias. The dashed black vertical line identifies the IAT *d* scale cutoff of .15 that distinguishes between *little or no* White bias versus *slight* White bias. Shaded areas represent 95% confidence intervals for predicted probabilities. Black × Bias interaction term is statistically significant in log-odds scale for ISS but not OOS (see Table 4, Column 8, Panels A and B). IAT = implicit association test.

students and Black students. White/Black disciplinary gaps are larger among counties with higher levels of bias; these relationships appear to be primarily driven by greater probabilities of suspensions for Black students in counties with stronger bias and not necessarily by lower probabilities of suspensions for White students. When replicating models from Columns 1 and 3 for the subset of counties for which we can adjust teacher bias scores (Columns 4 and 5), we arrived at largely similar conclusions. Finally, our hypotheses are also supported when focusing on just teachers' biases: counties where teachers have a stronger preference for Whites have greater White/Black disciplinary gaps (Columns 6–8) even after including covariates.

To help put the numbers in Table 4 into context, see Figure 1, where we plot predicted probabilities for suspension by race against bias (assuming mean values for all other covariates) using the coefficients from the models represented in Table 4 Panels A and B, Column 8 (note in this column that the interaction term in the log-odds scale is statistically significant for in-school suspensions but not out-of-school suspensions). From Figure 1, we see that Black students in counties with average teacher bias scores on the original IAT *d* score scale (.36) have respective predicted probabilities of in- or out-of-school suspensions of approximately 13% and 16%; for White students, these are about 5% for both outcomes. For a county at the cutoff between little or no bias toward Whites and slight bias (.15), the analogous predicted probabilities for in- or out-of-school suspensions are closer: For Black students, they are about 8%; for White students, they are 4% and 2%. Although no counties in our sample have implicit bias estimates of zero (i.e., no preference for either Whites or Blacks), extrapolation suggests that these disciplinary disparities would be approaching zero.

Discussion

Few studies have measured and explored correlates of the implicit racial biases of educators in the United States, and fewer have linked teachers' biases to student outcomes. In this study, we found that teachers' implicit White/Black biases vary depending on teacher gender and race/ethnicity: Female teachers appear slightly less biased than nonfemale teachers, and teachers of color appear less biased than White teachers. In general, our contextual and instructional variables are weakly associated with teachers' implicit biases, although teachers tend to show lower adjusted levels of bias in counties with larger shares of Black students. Overall, counties with higher aggregate levels of implicit and explicit bias tended to have larger adjusted White/Black suspension disparities. For test-score inequalities, we found no adjusted association between county-level aggregate bias and White/Black test-score disparities. However, when we focused on the aggregate biases of teachers specifically, we found that counties with higher levels of pro-White/anti-Black bias among teachers tended to show larger Black/White disparities in both test scores and suspensions after adjusting for a wide range of county-level covariates. Before further interpreting these results, we consider some data limitations.

Data Limitations

As noted earlier, one limitation of the study is the self-selection of respondents into the Project Implicit data. Although we adjusted county-level bias scores to account for the nonrepresentativeness of the IAT respondent sample based on observable differences, if stratification weights fail to capture important unobserved determinants of implicit bias, any county-level estimates may still be biased. For example, people particularly aware of their own implicit racial biases may be taking the race IAT—this may bias estimates of implicit preferences toward Whites downward (if awareness is correlated with lower bias). Another possibility is that school districts with especially significant inequality may be compelling their staffs to take the race IAT as a launching point for professional development targeting implicitly held attitudes and stereotypes. We therefore urge caution when interpreting or generalizing our findings regarding the implicit racial biases of educators. In addition, the county identifiers we used to link Project Implicit data with SEDA and CRDC identified where teachers completed the IAT; we cannot confirm these are the counties in which they actually teach. With these limitations in mind, we proceed with interpreting our results.

Interpreting Descriptive Results

It is somewhat reassuring to see that teachers in counties with larger shares of Black students have relatively lower levels of implicit bias because the reverse would be worrisome. Of course, the explanation for this association cannot be determined from these data. Teachers with lower levels of implicit anti-Black bias may be more interested in working in counties with more Black students, may be more likely to remain teaching in these counties over time, or may be more likely to be hired in these counties. Teachers may also become less biased over time by working in counties with more Black students.

For Research Question 2, where we investigated the relationships between bias and White-Black test-score and suspension disparities, our results are consistent with theory. As hypothesized, test-score differences are larger in counties in which teachers show stronger preferences for Whites. These results depend on including county-level covariates in models, stressing the need to consider contextual differences across counties when relating bias to outcomes. We similarly found that the Black/White discipline gap is larger in counties with stronger preferences for Whites. These results for discipline outcomes generally converge with those from Riddle and Sinclair (2019)—the only existing study on this topic—despite analytic differences (e.g., we focused on the biases of all respondents and not just White respondents, used slightly different covariates in our MrP model, and used data from all CRDC years).

Bias and Student Outcomes: Theoretical Implications

As noted, we are only able to examine, in an exploratory manner, the noncausal associations between aggregate bias and student outcomes. The self-selection of respondents into the Project Implicit data prevents us from confidently generalizing about the levels of implicit bias in particular counties. In addition, our design does not allow us to describe the causal mechanisms behind any observed associations in the data. Instead, our results raise questions that should be explored in future research.

According to the bias of crowds theory, the racial context in which one is embedded influences one's automatic racial associations. The implicit bias scores of people within a county therefore provide information about the racial context of that county rather than simply describing stable, independent attitudes of people who happen to reside in that county. Although Project Implicit respondents are a self-selected group, the bias of crowds theory suggests that their aggregate biases proxy for structural forces that lead to unequal outcomes by race: Their implicit bias is "a psychological marker of systemic prejudice in the environment" (Payne et al., 2017, p. 239). In counties where Black residents face more discrimination and more formidable structural barriers (e.g., economic and housing opportunities, disproportionate policing), negative stereotypes of Black Americans will be more accessible in the minds of IAT test-takers. Implicit bias can then serve as a mechanism that converts systemic prejudice into individual acts of discrimination (Payne et al., 2017). Thus, observed associations between aggregate biases and student outcomes may arise partly from students' experiences of racial discrimination in or out of school and partly from the structural forces that jointly produce racial bias and inequalities in educational outcomes. Indeed, controlling for White/Black disparities on covariate measures attenuated relationships between bias and test-score and suspension disparities, more so for the former outcome. At the same time, the vast majority of the variation in teachers' (and nonteachers') implicit biases resides within counties (Table 2). This may indicate that a level of analysis lower than the county is necessary when applying the bias of crowds theory. For example, teacher bias may vary more at the school level, and school-level teacher bias may more strongly correlate with school-level racial disparities in student outcomes.

Future Directions

One natural extension of our study would be to look beyond this article's focus on individuals' racial attitudes toward Black Americans and examine measures of bias toward other groups to understand how they influence other students' outcomes. Furthermore, because race is socially constructed and thus changes over time and across contexts (Haney López, 1994), the work of developing measures of bias and investigating their impacts need to be ongoing.

Future quantitative work should specifically seek exogenous sources of variation in the implicit racial bias of educators to help determine whether they have direct, indirect, or proxy effects on student outcomes and help to uncover the level of analysis that is most meaningful for examining these questions. Finally, qualitative work (e.g., interviews with Black students and/or teachers) in particular can provide detailed insight unavailable from large quantitative studies on which of the theoretical mechanisms described in our literature review contribute most to relationships between teachers' bias and test-score and/or disciplinary outcomes.

Conclusion

This study responds to calls from education researchers and social psychologists for incorporating theory and measures of implicit racial bias into education research (Quinn, 2017; Warikoo et al., 2016). These calls are particularly pressing given, among other reasons, the projected growth in the population of K–12 students of color and the fact that present-day racist political rhetoric may be counteracting years of improvement in explicit (if not implicit) racial attitudes (e.g., Schaffner, 2020). Our findings serve as a foundation for future research on teachers' implicit racial biases and raise questions about the specific ways in which bias may contribute to racial disparities in educational outcomes both at the interpersonal and the aggregate levels.

NOTES

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[1]The implicit association test (IAT) uses the category labels *European American* and *African American*. We therefore use these terms when discussing components of the test specifically and *White* and *Black* otherwise.

[2]Approximately 19% of Project Implicit site visitors did not respond to the occupation question. The occupation variable does not differentiate between public or private school teachers.

[3]As we describe in more detail in the Analytic Plan section, for Research Question 2, we adjusted the county-level estimates of bias used as correlates of racial differences in outcomes to account for non-representativeness of the IAT respondent sample. For pooled bias scores (i.e., those using all respondents), we adjusted scores using American Community Survey data. For teacher bias scores, we adjusted scores for fewer counties due to data limitations, described in Appendix C (in the Supplemental Material available on the journal website). These limitations restricted county coverage, resulting in a common sample of counties representing approximately 33% and 36% of counties with K–12 teacher IAT data or student outcome gaps, respectively.

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